Congestion Forecasting in Wholesale Power Markets

Literature Survey presentation on 10/25/2013

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Outline:

• Challenges - Authors’ view on Transmission Congestion forecasting: Utmost need of the hour?
• Approaches used for Congestion forecasting by different Authors
• LMP and Congestion Forecasting: Intertwined?
Transmission Congestion forecasting: Need of the hour?
How different authors stressed the need for developing methods to compute Transmission Congestion Forecasting?

• The first and foremost reason – Deregulation of Power Markets.

• De-regulation brought in so many companies into trading activities thereby creating a competitive market Environment.
• Subsequently more short term trading activities started taking place.
• One of the reason for Short-term power trading is also overall increase in Non-base loads like Wind and Solar Energy.

• Also, unexpected Intra-day modifications in Power Markets makes Day-ahead forecast more complex.
• In an event of unforeseen Congestion, the electricity price shoots up thus putting the burden on Consumers also ISO’s purpose of ensuring reliable Power Supply to Consumers is defeated.

Also the other reasons for having Congestion Forecasting is that Load Variations could be introduced into the system in case of any Topological Modifications introduced in the Network associated with a particular region.

The best example for such a scenario is the European Transmission System Operator (TSO) in which many of the European Countries are part of a common Energy-trading Network.

Such a Network spread across geographical area is highly vulnerable to congestion thus prompting the need for having a forecast.
Example of Inter-connected European Network:
Jiri Vresky and Patrick Panciatichi, “Day ahead Congestion Forecast for the secure operation of European Transmission System”.

Standard deviation of aggregated flows: MW
Approaches used for Congestion forecasting:

Classification:

• Next-hour forecast / Short-term (Intra-day) forecast
• Day-ahead forecast
• Using Day-ahead LMP forecast to forecast Transmission Congestion
• Supply-side strategic behavior forecasts using Artificial Simulated agents

However, AC/DC OPF model, contingency analysis and historical data is used as a basis for all types of congestion forecast models and approaches
Next hour forecast / Short-term (Intra-day):


- In this method, the variables used for forecasting is separated into several separate time-series regression models for each hour using weather variables and specific market information.

- According to author, the idea of variable segmentation i.e. framing the problem as 24 separate hourly models renders each model rather more simple.

- Though it involves more parameters and is computationally intensive, this method allows different variables to have different response functions for each hour.
Next hour forecast / Short-term (Intra-day):

• The other approaches discussed by the same author was:

> Combination of Forecasts: Based on identification of different models, a statistically more accurate forecast can be obtained through a linear combination of their outputs.

> Load forecasting with Neural Networks
Next hour forecast / Short-term (Intra-day):

• In the research paper by Q. Zhou, L. Tesfatsion, and C. C. Liu, “Global sensitivity analysis for the short-term prediction of system variables,” in *Proc. IEEE PES General Meeting 2010*, Minneapolis, MN, Jul. 29, 2010, the author’s have developed a Prediction Algorithm based on Sensitivity Matrix, System pattern applied to DC OPF formulation and the Linear relationship of variables.

  • \( \text{LMP} = \mathbf{F}(\text{L}) \) (1)
  • \( \text{LMP} = [\text{LMP}_1, \text{LMP}_2, \ldots, \text{LMP}_N]^T \) (2)
  • \( \text{L} = [L_1, L_2, \ldots, L_N]^T \) (3)
• In these equations, $N$ denotes the number of buses, $LMP_i$ denotes the LMP at bus $i$, and $L_i$ denotes the load at bus $i$.

• The Jacobian matrix formed corresponding to equation(4) is:

$$
J = \begin{bmatrix}
\frac{\partial F_1}{\partial L_1} & \cdots & \frac{\partial F_1}{\partial L_N} \\
\vdots & \ddots & \vdots \\
\frac{\partial F_N}{\partial L_1} & \cdots & \frac{\partial F_N}{\partial L_N}
\end{bmatrix}
$$
• This Jacobian matrix is derived at a system operating point for a given distributed load pattern.
• The linear approximation of function (1) at this operating point can be expressed as follows:

$$\Delta LMP = J \cdot \Delta L \ (5)$$

• Moreover, the derivation of the Jacobian matrix (4) can be extended to encompass rates of change with regard to unit dispatch levels, transmission line power flows, and line shadow prices, in addition to LMPs.
• Also, the author uses System patterns in terms of the dispatch states of generation units and the congestion states of transmission lines.

• Specifically, each generation unit is categorized as dispatched at minimum capacity / maximum capacity or partially dispatched.

• In the flowing System pattern table, flags are used to denote the states of generation units and transmission lines:

<table>
<thead>
<tr>
<th>Flags used for system patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td>State</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>Flag</td>
</tr>
</tbody>
</table>
Based on the DC OPF Formulation and Linear relations, the following prediction method is proposed:

1. **Required historical data**
2. Determine all historical system patterns
3. Calculate sensitivity matrix for each pattern
4. Set $t=1$ for the first forecasting period
5. Forecasted load input
6. Set $i=1$
7. Assume system pattern at time $t$ is $i$
8. Calculate generation dispatch and line flow using the corresponding sensitivity matrix
9. Results violate the assumption?
   - Yes: $i=i+1$
   - No: The results are used as the forecasts
10. $t=t+1$
11. $t=T$?
    - Yes: End of forecasting
    - No: Repeat from step 5

• In one of the research paper by L. Min, S. T. Lee, P. Zhang, V. Rose, and J. Cole, “Short-term probabilistic transmission congestion forecasting,” in Proc. IEEE DPRT 2008, Nanjing, China, Apr. 2008, the authors have applied sequential Monte Carlo Simulation to Probabilistic Load Flow.

• It was achieved by using the following steps:

1. Load Uncertainty Modeling

2. Co-relation between loads and sampling technique modeling

3. Probabilistic model of Generation and

4. Probabilistic model of Transmission Contingency
Day-ahead congestion forecasting:

- It is the widely followed approach towards dealing with congestion forecasting.
- In the research paper by C. Barbulescu, et. al. “Deregulated Power Market Congestion Management”, the authors have used variables, constraints and objective function in the OPF equation as a mathematical model for applying them to Probabilistic Approach.
- The following steps are carried out:
  1. Probabilistic modelling of consumed powers
  2. Random contingencies analysis
  3. Sample Acceptance

The authors developed a software tool to run the process and the results were available for each of the congested branch:

A. Sample containing the Congested branch
B. The contingency scenario’s considered

- The other methods used are to find day-ahead forecast values using Standard deviation and Probabilistic distribution based on Network models.
Using Day-ahead LMP prices forecast to forecast Transmission Congestion:

- In one of the research paper, G.Li, C.C.Liu and H.Salazar “Forecasting Transmission Congestion using Day-Ahead Shadow Prices”, authors had interestingly used the day-ahead Shadow price forecast for forecasting day-ahead Transmission Congestion.

- In this paper, the authors apply a factor-model approach to a grid environment that uses LMP and then LSE is implementation is done to simplify the parameterization of time series factor modeling.

- As the factor-model provides interpretability, the same is used for prediction of day-ahead congestion conditions.

- The shadow price multiplied by the power flow on the constrained facility during each hour is the hourly gross congestion cost for the constraint.

- Thus, the author develops a model to forecast congestion based on Intertwining property of LMP Pricing and Congestion
Summary of Error values of different models for Transmission Congestion:

- Research paper by A.Loland, E.Ferkingstad and M.Wilhelmsen, “Forecasting Transmission Congestion”, The Journal of Energy Markets, Vol. 5 No.3, the authors have applied various models to a system to determine the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for different models.
- Author also used combination of different models to consider their weighted sum in order to summarize the error table.
<table>
<thead>
<tr>
<th>Years</th>
<th>Hour</th>
<th>Measure</th>
<th>Naive 1</th>
<th>Naive 7</th>
<th>Naive 137</th>
<th>Expsm</th>
<th>TAR</th>
<th>ARIMA 200</th>
<th>ARIMA 210</th>
<th>ARIMA</th>
<th>CB₁</th>
<th>CB₂</th>
<th>CB₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003-9</td>
<td>1-24</td>
<td>RMSE</td>
<td>0.41</td>
<td>0.41</td>
<td>0.34</td>
<td>0.31</td>
<td>0.32</td>
<td>0.30</td>
<td>0.30</td>
<td>0.38</td>
<td>0.30</td>
<td>0.29</td>
<td>0.29</td>
</tr>
<tr>
<td>2003-4</td>
<td>1-24</td>
<td>RMSE</td>
<td>0.37</td>
<td>0.36</td>
<td>0.28</td>
<td>0.26</td>
<td>0.27</td>
<td>0.26</td>
<td>0.27</td>
<td>0.34</td>
<td>0.26</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>2005-6</td>
<td>1-24</td>
<td>RMSE</td>
<td>0.44</td>
<td>0.44</td>
<td>0.37</td>
<td>0.34</td>
<td>0.34</td>
<td>0.32</td>
<td>0.31</td>
<td>0.41</td>
<td>0.32</td>
<td>0.31</td>
<td>0.31</td>
</tr>
<tr>
<td>2007-9</td>
<td>1-24</td>
<td>RMSE</td>
<td>0.40</td>
<td>0.42</td>
<td>0.35</td>
<td>0.32</td>
<td>0.33</td>
<td>0.30</td>
<td>0.31</td>
<td>0.38</td>
<td>0.30</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>2003-9</td>
<td>1-24</td>
<td>MAE</td>
<td>0.26</td>
<td>0.28</td>
<td>0.22</td>
<td>0.21</td>
<td>0.22</td>
<td>0.21</td>
<td>0.21</td>
<td>0.28</td>
<td>0.20</td>
<td>0.20</td>
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<td>MAE</td>
<td>0.25</td>
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<td>0.18</td>
<td>0.18</td>
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<td>1-24</td>
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<td>0.30</td>
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<td>0.19</td>
<td>0.19</td>
</tr>
</tbody>
</table>

The following abbreviations are used: Naïve 1 (yesterday’s value), Naïve 7 (last week’s value), Naïve 137 (semi-naïve), Expsm (exponential smoothing), TAR (piecewise linear threshold autoregression), ARIMA 200 (ARIMA(2,0,0)), ARIMA 210 (ARIMA(2,1,0)), ARIMA (naïve ARIMA(1,0,0)), CB₁ (combination model 1; simple average), CB₂ (combination model 2; weighted sum with respect to estimated prediction error variances), CB₃ (combination model 3, weighted sum with respect to previous performance).
Thank You

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